REMARKS

Applicant respectfully requests reconsideration of this application as amended. Claims 1-30 remain in the application. No claims have been canceled. Attached hereto is a marked-up version of the changes made to the specification by the current amendment. The attached page is captioned "Versions with markings to show changes made."

Objections to the Specification

The Examiner requested correction of certain informalities in the specification. In response, Applicant has amended the specification accordingly. No new matter has been added.

In addition, as a practitioner representing the applicant, I declare, the amendatory material included to amend the disclosure to include the material incorporated by reference consists of the same material incorporated by reference in the referencing application.

Claim Rejections – 35 USC §102

Claims 24-27 were rejected under 35 U.S.C. §102(e) as being anticipated by Luke et al., US Patent number 6,131,087 ("Luke"). The Applicant does not admit that the Luke reference is prior art and reserves the right to swear behind the reference at a later date. Nonetheless, Applicant respectfully traverses the rejection because the Luke reference does not disclose each and every element of the invention as claimed in claims 24-27.

The Luke reference discloses a method of matching offer and solicitation data from market participants and notifying originators of the matching data of the results of any such matching operations. [Column 6, lines 12-19]. The solicitation data is expressed in terms of multiple dimensions of the transactions

that are expressed in numeric terms on a linear scale. [Column 5, lines 53-66]. Specifically, the matching system matches market participants according to the congruence of preferred points between the offer data and solicitation data. [Column 11, lines 29-34].

In contrast, claim 24 claims a method of generating multi-attribute bids, comprising:

collecting at least one set of multi-attribute bid values, each set of multi-attribute bid values having a set of nominal attribute values including a nominal bid value, said collecting also includes collecting at least one variance to the nominal attribute value of at least one attribute and a corresponding variance relative to said nominal bid value;

generating a set of bids for each set of multi-attribute bid values, each bid having a different combination of attribute values based on corresponding variances and nominal attribute values; and

generating a bid value for each bid based upon the combination of attribute values.

The Luke reference does not perform the element of "generating a bid value for each bid based upon the combination of attribute values." In Luke, given the multiple dimensions of a transaction, a graphical example of the solicitations is made. [Figure 1a and 1b]. As shown in figure 1b of the Luke reference, the intersecting points of solicitations, define the boundaries of negotiation 40 between the originator of the offer and the originator of the solicitation. Also, the shaded polyhedron 40 is the transaction space, i.e., the space within which the parties can bargain to complete an exchange. [column 6, lines 20-34]. The Luke reference does not generate **a bid value**, as claimed, based upon the combination of attribute values given the combination of attribute

values based corresponding variances and nominal attribute values. That is, the bid values of buyers and sellers in the Luke reference are not generated based on the variance of at least one of the given attributes. The Luke reference only disclosures the generation of geometric objects (e.g., polyhedrons) to find a bargaining point to begin negotiations and does not teach the element of generating "a bid value for each bid based upon the combination of attribute values", as claimed.

Accordingly, Applicant submits that claim 24 is not anticipated by the Luke reference under 35 USC §102(e) and respectfully requests the withdrawal of the rejection of the claim. Claims 25-27 are dependent on claim 24, therefore, at least for the reasons stated above, it is respectfully submitted these claims are allowable over the cited prior art.

Claim Rejections – 35 USC §103

Claims 1-23 and 28-30 were rejected under 35 U.S.C. §103(a) as being obvious over Luke et al, US patent number 6,131,087 ("Luke") in view of Buss et al., US patent number 5,841,958 ("Buss").

Claim 1

Claim 1 claims a method of matching at least one multi-attribute bid from one or more buyers and at least one multi-attribute bid from one or more sellers, comprising:

selecting a pair of bids between each buyer and each seller, the pair of bids having a highest surplus;

generating a weighted bipartite graph comprising buyer nodes and seller nodes and an edge between each buyer node and each seller node, each edge

having the highest surplus of the pair of bids between the buyer and seller as a weight; and

determining maximal weighted matching bids from the highest surplus pairs of bids using the weighted bipartite graph.

The office action states that the Luke reference "does not explicitly disclose the use of a weighted bipartite graph comprising buyer nodes and seller nodes and an edge between each buyer node and each seller node, each edge having the highest surplus of the pair of bids between the buyer and seller as a weigh." However, the office action continues that it would have been within the level of ordinary skill in the art to modify the method of Luke by adopting the teaching of Buss that discloses the use of a bipartite graph for matching objects of one subset with objects of a different subset where multiple choices are permitted to provide a more efficient and faster process.

According to the MPEP §2143.01, "obviousness can only be established by combining or modifying the teachings of the prior art to produce the claimed invention where there is some teaching, suggestion, or motivation to do so found either explicitly or implicitly in the references themselves or in the knowledge generally available to one of ordinary skill in the art." Here, the Buss reference teaches a computer technique for bipartite matching of objects but does not teach or suggest that such a method may be used in an electronic marketplace environment to match one or more buyers and at least one multi-attribute bid from one or more sellers as claimed. Furthermore, the Luke reference teaches the use of intersecting points of polyhedron geometric objects to define the boundaries of negotiation between the originator of the offer and the originator of the solicitation of the multiple dimensions of a transaction. [column 6, lines 21-34]. The Luke reference does not contain a teaching, suggestion, or motivation that a weighted bipartite graph may be used in "determining maximal weighted

matching bids from the highest surplus pairs of bids using the weighted bipartite graph," as claimed. This is because the Luke reference does not required "maximal weighted matching bids" to determine a match because the Luke reference generates overlapping geometric objects (figure 1a and 1b) to determine which buyers and sellers having matching attributes.

In addition, the mere fact that Luke reference uses a specific method (e.g., geometric objects) to associate multiple buyers and sellers based on multiple attributes does not mean that it would be obvious to one of ordinary skill in the art to use a bipartite graph, as claimed. The Luke reference must suggest the desirability of the combination. "The mere fact that references must be combined or modified does not render the resultant combination obvious unless the prior art also suggests the desirability of the combination." [MPEP 2143.01].

As neither the Luke reference, nor the Buss reference teach or suggest the use of a weighted bipartite graph in a method of matching at least one multi-attribute bid from one or more buyers and at least one multi-attribute bid from one or more sellers, as claimed in claim 1, the combination cannot be interpreted to disclose the claimed element. Accordingly, Applicant respectively requests the withdrawal of the rejection of claim 1 under 35 USC §103(a) over the combination. Claims 2-15 are dependent on claim 1 and therefore, at least for the reasons stated above, it is respectfully requested that the rejection of claims 2-15 be withdrawn.

Claims 16 and 28

Claim 16 claims a dynamic trading method, comprising:

collecting at least one set of multi-attribute bid values from one or more buyers and at least one set multi-attribute bid values from one or more sellers;

generating buyer bids from said at least one set of buyer multi-attribute bid values and seller bids from said at least each set of seller multi-attribute bid values; and

selecting a pair of compatible bids between each buyer and each seller, the pair of bids having a highest difference in bid values.

Neither the Luke reference, the Buss reference, of a combination thereof, disclose a method of "generating buyer bids from said at least one set of buyer multi-attribute bid values and seller bids from the at least each set of seller multi-attribute bid values." The Luke reference does not generate bids based on the attributes but rather generates a geometric object of the offer and solicitation attributes and uses the overlapping portions of those geometric objects to determine which buyer and seller match. [column 6, lines 12-34]. The Luke reference applies the given price and does not adjust the price based on the attributes to generate a bid. Because the Luke and Buss combination does not teach the use of "generating buyer bids from said at least one set of buyer multi-attribute bid values and seller bids from the at least each set of seller multi-attribute bid values", the Luke reference could not further teach "selecting pair of compatible bids between each buyer and each seller, the pair of bids having a highest difference in bid values", as claimed, because it does not generate a bid, as stated. Therefore, the combination of Luke and Buss references also does not and could not teach that the match of a buyer and a seller based on selecting "the pair of bids having a highest difference in bid values", as claimed, because these reference do not teach the generation of bids.

Accordingly, Applicant respectfully submits that Applicant's invention as claimed in claim 16 is not rendered obvious by Luke in view of Buss, and respectfully request the withdrawal of the rejection under 35 USC §103(a).

Applicant's independent Claim 28 contains limitations similar to those contained in claim 16. Claims 17-23 and 29-30 are each dependent on one of the claims 16 and 28. Therefore, at least for the reasons stated above, the Applicant respectfully request withdrawal of the rejection to these claims.

Conclusion

Applicant respectfully submits that the rejections have been overcome by the amendments and remarks, and that the Claims as amended are now in condition for allowance. Accordingly, Applicant respectfully requests the rejections be withdrawn and the Claims as amended be allowed.Invitation for a telephone interview

The Examiner is invited to call the undersigned at 408-720-8300 if there remains any issue with allowance of this case.

Charge our Deposit Account

Please charge any shortage to our Deposit Account No. 02-2666.

Respectfully submitted,

BLAKELY, SOKOLOFF, TAYLOR & ZAFMAN LLP

Date: April 12, 2002

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VERSION WITH MARKINGS TO SHOW CHANGES MADE

In the Specification:

Paragraph beginning at page 10, lines 18 has been amended as follows:

The input screen 300 allows the [seller] buyer to specify a nominal set of values for the predefined attributes, including a nominal price, in the Nominal Value column. In addition, input screen 300 allows the seller to specify variances to the nominal attribute in the Variances column, if desired. Preferably, the variances are specified relative to the nominal price. The nominal price as well as the variances specified relative to the nominal price are preferably specified in terms of a uniform measure. More preferably, the uniform measure is a monetary measurement, such as U.S. dollars or any other currency.

Paragraph beginning at page 11, lines 12 has been amended as follows:

The variances to the attributes may be expressed in a number of ways and need not vary linearly relative to price. In the example shown in **FIG. 3**, the [seller] buyer specifies a nominal value of 5 for Quality 1 and the variances to Quality 1 are such that each unit of decrease in the value of Quality 1 results in an increase of 10 in price relative the nominal price of 100, up to a maximum increase of 20 for any lower value of Quality 1. In this example, Quality 1 is a negative quantity attribute, such as features size for a semiconductor chip, i.e. a lower numerical quantity represents a better product or service. Thus, if the minimum value of Quality 1 is 1, then Quality 1 values of 1, 2, or 3 all result in an

increase of 20 relative to the nominal price of 100. Further, by not specifying values of Quality 1 greater than 6, the market system preferably deems that all bids having values greater than 6 of Quality 1 would not satisfy or match the set of bids represented by the input screen 300.

Paragraph beginning at page 18, line 3 has been amended as follows:

For each pair of matching buyer-seller bids, a surplus is determined in step 708. The surplus is the difference between the buyer price and the seller price for a given matching buyer-seller pair of bids, the [buyer] <u>seller</u> price being less than or equal to the [seller] <u>buyer</u> price. For each buyer-seller pair, a matching pair of bids having a highest surplus among all matching bids of the buyer-seller pair is selected in step 710.

Paragraph beginning at page 20, line 1 has been amended as follows:

As shown, the maximal weighted matching <u>900</u> includes edges 902, 904, and 906 such that the combination of the best matches between Buyer A and Seller A, Buyer B and Seller C, and Buyer D and Seller B results in a highest overall surplus. The Added Seller is not part of the maximal weighted matching <u>900</u> because all edges to the Added Seller have a weight of 0 and thus the Added Seller does not contribute to the overall surplus.

Paragraph beginning at page 19, line 15 has been amended as follows:

Where there are no matching bids between a buyer and a seller, an edge having a weight of 0 may nonetheless be added. However, if there are no

matching bids between a buyer and any of the sellers (or between a seller and any of the buyers), the corresponding buyer (or seller) node may be removed from the weighted bipartite graph 800. If after the removal of all unmatched buyers and/or sellers there are an unequal number of buyers and sellers, a dummy or added buyer or seller node is preferably added to the set of nodes such that there are an equal number of buyer and seller nodes. Thus, given N number of resulting buyer nodes and N number of resulting seller nodes, the weighted bipartite graph 800 preferably includes a total of N^2 edges.

A paragraph was added beginning at page 20, line 15 as follows:

Determination of the maximal weighted matching of a weighted bipartite graph, also known as the assignment problem, is well known to those of ordinary skill in the art and described, in for example, Ahuja, Ravindra K., Thomas L. Magnanti, and James B. Orlin, "Network Flows: Theory, Algorithms, and Applications," 1993, (see, in particular Section 12.4)[, incorporated by reference herein]. The Ahuja reference discloses the bipartite weighted matching problem: given a weighted bipartite network $G = (N_1 \cup N_2, A) with\ |N_1| = |N_2|$ and arc weights c_{ij}, finds a perfect matching of minimum weight. Here, the network *G* is directed or undirected. If the network is directed, for each arc $(i, j) \in A,\ i \in N_1\ \ and\ \ j \in N_2$. If the network is undirected, the network is made directed by designating all arcs as pointing from the nodes in N_1 to those in N_2. Therefore, the following examples assume that *G* is a directed graph.

The assignment problem is a special case of the minimum cost flow problem and can be stated as the following linear program.

$$\text{Minimize} \sum_{\{j:(i,j)\in A\}} c_{ij} x_{ij}$$

subject to

$$\sum_{\{j:(i,j)\in A\}} x_{ij} = 1 \quad \text{for all } i \in N_1,$$

$$\sum_{\{j:(i,j)\in A\}} x_{ij} = 1 \quad \text{for all } i \in N_2,$$

$$x_{ij} \geq 0 \quad \text{for all } (i, j) \in A.$$

Since the weighted bipartite matching problem may be formulated as this special type of flow problem, it is not too surprising to learn that most algorithms for the assignment problem can be viewed as adaptations of algorithms for the minimum cost flow problem. However, the special structure of the assignment problem often permits simplification of these algorithms and to obtain improved bounds on their running times.

One popular algorithm for the assignment problem is a specialization of the network simplex algorithm and the successive shortest path algorithm and its many variants, that are well known to those of ordinary skill in the art. Examples of algorithms to solve a maximal weighted matching or assignment problem include specialization of a network simplex algorithm, successive shortest path algorithm, Hungarian algorithm, relaxation algorithm, and cost scaling algorithm for a minimum cost flow problem, as will be further described below. Many of these algorithms can be viewed as various adaptations of algorithms for a minimum cost flow problem. Any such or other suitable algorithms may be utilized to determine the maximal weighted matching of multi-attribute bids. The following briefly describe some of these successive shortest path-based algorithms and the cost scaling algorithm.

The successive shortest path algorithm, which is well known to those of ordinary skill in the art, obtains shortest path distances from a supply node to all other nodes in a residual network, uses these distances to update node

potentials and then augments flow from that supply node to a demand node. The successive shortest path algorithm, when applied to the assignment problem, would augment one unit flow in every iteration, which would amount to assigning one additional node in N_1. Consequently, if $S(n, m, C)$ denotes the time needed to solve a shortest path problem with nonnegative arc lengths and $n_1 = | N_1 1 |$, the algorithm would terminate within n_1 iterations and would require $O(n_1 S(n, m, C))$ time.

The Hungarian algorithm, which is well known to those of ordinary skill in the art, is a direct implementation of the primal-dual algorithm for the minimum cost flow problem. The primal-dual algorithm first transforms the minimum cost flow problem into a problem with a single supply node s^* and a single demand node t^*. At every iteration, the primal-dual algorithm computes shortest path distances from s^* to all other nodes, updates node potentials, and then solves a maximum flow problem that sends the maximum possible flow from node s^* to node t^* over arcs with zero reduced costs. When applied to the assignment problem, this algorithm terminates within n_1 iterations since each iteration sends at least one unit of flow, and hence assigns at least one additional node in N_1. The time required to solve shortest path problems in all these iterations is $O(n_1 S(n, m, C))$. Next consider the total time required to establish maximum flows. The labeling algorithm for solving the maximum flow problem would require a total of $O(nm)$ time because it would perform n augmentations and each augmentation requires $O(m)$ time. The dominant portion of these computations is the time required to solve shortest path problems. Consequently, the overall running time of the algorithm is $O(n_1 S(n, m, C))$.

The relaxation algorithm, which is closely related to the successive shortest path algorithm, is also well known to those of ordinary skill in the art and is another popular approach for solving the assignment problem. This algorithm

relaxes the constraint $\sum_{\{j:(i,j)\in A\}} x_{ij} = 1$ for all $i \in N_2$, thus allowing any node in N_2 to be assigned to more than one node in N_1. To solve the relaxed problem: Assign each node $i \in N_1$ to any node $j \in N_2$ with the minimum cost c_{ij} among all arcs in $A(i)$. As a result, some nodes in N_2 might be unassigned while some other nodes are over assigned (i.e., assigned to more than one node in N_1). The algorithm then gradually converts this solution to a feasible assignment while always maintaining the reduced cost optimality condition. At each iteration the algorithm selects an over-assigned node k in N_2, obtains shortest path distances from node k to all other nodes in a residual network with reduced costs as arc lengths, updates node potentials, and augments a unit flow from node k to an unassigned node in N_2 along the shortest path. Since each iteration assigns one more node in N_2 and never converts any assigned node into an unassigned node, within n_1 such iterations, the algorithm obtains a feasible assignment. The relaxation algorithm maintains optimality conditions throughout. Therefore, the shortest path problems have nonnegative arc lengths, and the overall running time of the algorithm is $O(n_1 S(n, m, C))$.

The cost scaling algorithm, which is well known to those of ordinary skill in the art, is an adaptation of the cost scaling algorithm for the minimum cost flow problem. The cost scaling algorithm performs $O(nC))$ scaling phases and the generic implementation requires $O(n^2 m)$ time for each scaling phase. The bottleneck operation in each scaling phase is performing nonsaturating pushes which require $O(n^2 m)$ time; all other operations, such as finding admissible arcs and performing saturating pushes, require $O(nm)$ time. When applying the cost scaling algorithm to the assignment problem, each push is a saturating push since each arc capacity is one. Consequently, the cost scaling algorithm solves the assignment problem in $O(nm \log(nC))$ time.

A modified version of the cost scaling algorithm has an improved running time of $O(\sqrt{n}\, m \log(nC))$, which is the best available time bound for assignment problems satisfying the similarity assumption. This improvement rests on decomposing the computations in each scaling phase into two subphases. In the first subphase, apply the usual cost scaling algorithm is applied with the difference that whenever a node is relabeled more than $2\sqrt{n}$ times, this node is set aside and not examined further. When all (remaining) active nodes have been set aside, the second subphase is initiated. It is possible to show that the first subphase requires $O(\sqrt{n_1}\, m)$ time, and when it ends, the network will contain at most $O(\sqrt{n_1})$ active nodes. The second subphase makes these active nodes inactive by identifying "appropriate shortest paths" from nodes with excesses to nodes with deficits and augmenting unit flow along these paths. The algorithm uses Dial's algorithm to identify each such path in *O(m)* time. Consequently, the second subphase also runs in $O(\sqrt{n_1}\, m \log(nC))$.